INDIVIDUAL TREE SPECIES CLASSIFICATION AT THE ACADIA RESEARCH FOREST USING AIRBORNE LIDAR

by

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ABSTRACT

Species knowledge is an essential component of any accurate forest inventory. In this study, 14 Acadian tree species were remotely classified with the Random Forests classifier using two LiDAR datasets (1 pulse per m^2 and 6 pulses per m^2). The 6 pulses per m^2 dataset was found to perform better for individual tree species identification with 11.1 % higher overall accuracy (1 pulse per m^2 accuracy = 32.8 %, 6 pulses per m^2 = 43.9 %). Additional modeling strategies were explored to further boost accuracy, including aggregating species by product market class (+ 16.9 % increase in accuracy) and adding contextual features such as elevation, depth to water and site information (+ 6.9 %). Further improvements were possible by using a multi-step hierarchical species-group modeling approach (+ 3.4 % for softwood groups to 71.1 % overall accuracy and +16.1 % for hardwoods to 83.8 % overall accuracy). To further boost accuracy to an operational level, higher pulse density and/or additional variables including multi-spectral and multi-temporal imagery should be explored.

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List of Symbols and Abbreviations

ABA: Area Based Approach

ALS: Airborne Laser Scanning

ARF: Acadia Research Forest

ASPRS: American Society for Photogrammetry and Remote Sensing

CHM: Canopy Height Model

CWFC: Canadian Wood Fibre Centre

DBH: Diameter at Breast Height

GPS: Global Positioning System

KNN: K-Nearest Neighbour

SVM: Support Vector Machines

RF: Random Forests

LDA: Linear Discriminant Analysis

NPD: Nominal Pulse Density

LiDAR: Light Detection and Ranging

Introduction

In recent years, LiDAR (Light Detection and Ranging) has become a valuable tool used by forest practitioners providing a wealth of information that can be used to characterize forest structure and topography (White et al. 2016; Coops et al. 2021). In the case of airborne LiDAR, also known as Airborne Laser Scanning (ALS), laser pulses are emitted from a sensor on an aircraft scanning a swath of the earth's surface. When these pulses come into contact with objects, some or all of the emitted light is reflected back to the sensor, where the time to return and the aircraft's exact Global Positioning System (GPS) location and altitude allows the point of return to be recorded in 3-dimensional space. The aggregation of these coordinates is referred to as a 3D point cloud and is stored as a LAS data file (ASPRS 2003). Nominal Pulse Density (NPD) refers to the number of points per unit area, usually expressed as pulses per square meter m^2 (ASPRS 2005).

Through advances in research and technology, it has become feasible to correlate point cloud statistics with many of the stand-level forest inventory variables used in forest management decision making (Woods et al. 2011; Treitz et al. 2012; White et al. 2013). Point clouds for entire forest estates are scaled up and gridded into prediction units or grid cells, each commonly 20 x 20 m, and model-based predictions of forest metrics such as gross total volume, merchantable volume, basal area, quadratic mean diameter, height, and stem density are made for each cell. This is known as the area-based approach (ABA) to LiDAR-derived forest inventory and has been proven to be feasible for

operational forest management and planning in several jurisdictions (White et al. 2013; Wulder et al. 2013; Naesset 2015).

Knowledge of species composition is an essential attribute of any forest inventory. In addition to its economic value for the estimation of forest product volume, species is important for the assessment of carbon stocks (Dalaponte and Coomes 2016), ecological integrity (Casas et al. 2016), forest health and biodiversity (Bradbury et al. 2005; Kim et al. 2009; Bright et al. 2012; Vastaranta et al. 2013). Effective and efficient forest management demands accurate and up-to-date information on the various attributes of the growing stock (Wulder et al. 2008; Yu et al. 2011; White et al. 2016). Foresters can apply species-specific allometric models to improve estimates of current and projected volumes of timber or above ground biomass (Lambert et al. 2005; Tompalski et al. 2014), thus optimizing stand management strategies including silviculture prescriptions (Pitt and Pinneau 2009).

Since the early 1940's, species knowledge for forestry applications has been obtained from the manual interpretation of aerial photography (Parry 1973). Losee pioneered the development of methods to identify eastern Canadian tree species from aerial photography through their visible characteristics (Losee 1942a; Losee 1942b; Parry 1973). Despite being expensive, subjective and time consuming, this method is still widely used today (Leckie et al. 1999). There have been many attempts to overcome these shortcomings by automating species classification, starting with airborne and spaceborne imagery (Gougeon 1995; Gougeon and Leckie 2006); then LiDAR, since the recent (~2011) advent and adoption of this technology for wall-to-wall quantification of stand structure (White et al. 2016). Studies attempting to predict species using airborne

LiDAR at the individual tree level have been carried out in a variety of forest types of differing levels of species complexity. Fassnacht et al. (2016) recommended that future tree species classification research focus on test acquisition parameters (pulse density in this case) and "focus stronger on the causal understanding of why species classification approaches work under certain conditions – maybe even more important – why they do not work in other cases".

Brandtberg et al. (2003) classified three hardwood species groups including oaks (*Quercus* spp.), red maple (*Acer rubrum* L.) and yellow poplar (*Liriodendron tuliperifera* L.) native to West Virginia. Classification accuracies were 50 % for oaks, 60 % for red maple and 70 % for yellow poplar, averaging 60 % overall. The ALS data were obtained in leaf-off conditions using on average 12 returns per square metre. The classification accuracy was further improved to 64 % in a subsequent analysis (Brandtberg 2007). Holmgren and Persson (2004) achieved up to 95 % accuracy when distinguishing between Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) Karst.) using approximately five pulses per square metre airborne LiDAR in boreal Scandinavia. Holmgren et al. (2008) used high density LiDAR (50 points per square metre) to classify Norway spruce, Scots pine and deciduous species primarily consisting of birch at a success rate of 88 %. In Central Europe, Reitberger et al. (2008) successfully distinguished Norway spruces, sycamore maples and European beeches at a rate of 85 % in leaf-on conditions and 96 % in leaf-off conditions. Ørka et al. (2009) correctly distinguished Norway spruce from birch species (77 % accuracy) using structural features derived from 6.6 points per square metre ALS data.

Random Forests (RF) (Breiman 2001), an ensemble classification method that uses decision trees as the base classifier (Breiman 2001), has been effectively used for species classification in many recent studies. Ko et al. (2013) correctly classified trees into pine, poplar and maple genera using RF at accuracies of 86, 88, and 93 %, respectively, using high density 40 pulses per m^2 airborne LiDAR. Yu et al. (2014) used a RF approach to classify boreal species in Finland using low density 1 pulse per m^2 discrete and full-waveform airborne LiDAR. Overall classification accuracy using discrete LiDAR was 62 % with individual species accuracies of 81 % for pine, 47 % for spruce, and 31 % for birch (Yu et al. 2014). Budei et al. (2018) used multispectral airborne LiDAR near Toronto, Canada to classify up to seven genera and 10 species using three wavelengths. They compared classification results derived from individual wavelength channels, and by aggregating all three. The infrared channel yielded on average 64 % prediction accuracy when classifying 10 species, with pulse density approximately three pulses per m^2 (Budei at al. 2018). In northwestern New Brunswick, Canada, Perron (2018) classified 10 Acadian forest tree species, genus, and deciduous/coniferous groups with 49, 58, and 93 % accuracy, respectively, using 6 pulses per m^2 airborne LiDAR. Percent accuracy here refers to the number of training crowns correctly classified relative to the total within a subset of crowns reserved for validation. More recently, in eastern Ontario, Canada, Prieur et al. (2022) correctly classified 12 tree species at an accuracy of 51 % using 6 pulses per m^2 airborne LiDAR. Also evaluated were functional group (hardwood, intolerant hardwood, other softwood, pine and spruce) accuracy at 69 %, four genera (maple, pine, poplar and spruce) at 75 % and deciduous/coniferous levels at 86 %.

Thus far, ALS data have been shown to have limitations for species identification (White et al. 2016). One active area of research that attempts to improve species identification focuses on point cloud geometry and dispersal at the individual tree crown level. Point cloud geometry can, with sufficient pulse densities, reflect the shape of individual tree crowns as determined by structure of the biomass in a particular tree or part thereof (Riaño et al. 2004; Coops et al. 2007; Ørka et al. 2009). Point cloud features may include crown width, crown length, branch angles, roundness/pointiness, vertical distribution of points and porosity (Riaño et al. 2004; Coops et al. 2007). Given that certain calculated features are characteristic of particular species, or species groups, they may enable predictions such as deciduous vs. coniferous, genus, and ultimately, species. Another feature recorded by LiDAR, intensity, can be described as the backscattering of a laser signal (Wehr and Lohr 1999). Intensity is an important factor when separating species, especially when used in combination with structural data (Holmgren and Persson 2004; Ørka et al. 2009). Kim et al. (2009) found that intensity values were related to both the reflective properties of foliage and to the arrangement of crown structure, including branches and can be used to distinguish broadleaf species from conifers. Spectral information from different sensors can also be combined with LiDAR data (Vaukhonen et al. 2014) to increase classification accuracy. This may be in the form of other remote sensing tools or platforms such as imagery, multispectral, or hyperspectral LiDAR.

Airborne LiDAR can be acquired at a range of different pulse densities for various applications. Pulse density is based on various factors such as flight altitude, topography, aircraft speed, overlap, pulse rate, scanning angle and swath width. Acquisition density specifications are defined by the client according to management

objectives, budget, previous coverage and timing. There is general consensus among researchers that single tree detection and species identification improves with higher density (up to 10 points per m^2) LiDAR (Reitberger et al. 2008; Yu et al. 2014; Hovi et al. 2016; Fussnacht et al. 2016). Suratno et al. (2009) and Yu et al. (2014) suggested that low-density discrete return LiDAR (less than 5 points per m^2) is of limited use for species prediction at the individual tree level. In contrast, Vauhkonen et al. (2008) found that pulse densities as low as 0.5 returns per m^2 were sufficient for identifying commercially important Finnish species at an individual tree level.

Several studies have suggested that tree size may affect classification results when using 3D point cloud features derived from their geometric shape and distribution (Ørka et al. 2009; Korpela et al. 2010; Hovi et al. 2016). Budei and St-Onge (2018) investigated the influence of tree size (height) on deciduous tree species identification using multispectral LiDAR and found a significant number of LiDAR features were correlated to height (R^2 up to 0.6). Further, they found intensity features tended to be highly correlated to tree height, even in the case of ratios or NDVIs (Normalized Difference Vegetation Indices).

Contextual features in a species classification context refer to the variables that form the setting (or total environment) for an event, statement, or idea (Fowells and Means 1990). The "total environment" of a tree is a complex integration of physical elements, which includes anything related to soil and climate, and biological elements, which are the associated plants, animals, insects, fungi and microorganisms. (Fowells and Means 1990). Silvics is defined by Merriam-Webster as "the study of the life history and characteristics of forest trees especially as they occur in stands and with particular

reference to environmental influences". A tree species silvics would therefore, be considered its propensity to grow in a given physical and biological environment and could be included as a feature in species classification.

The objectives of this study were: 1) to compare classification accuracies for 14 tree species, genus and hardwood/softwood groups, and size classes, using airborne LiDAR acquired at averages of 1 pulse per m^2 and 6 pulses per m^2 in an Acadian forest; 2) identify the most important features used for remote species classification using a RF model; 3) to test models that include contextual prediction variables including elevation, depth to water, and tree species ecological affinity (species ecological relative abundance rasters developed by FORUS Research (2019) as a function of location and topography throughout New Brunswick); and 4) to evaluate a multi-step modeling approach whereby hardwoods and softwoods are first separated and then species-specific hardwood and softwood models are developed.

The general hypotheses of this study were: 1) the 6 pulses per m^2 LiDAR dataset will result in greater classification accuracies than the 1 point per m^2 dataset in all levels of classification; 2) taller trees within training datasets will result in greater classification accuracies; 3) classification accuracies will improve with the addition of contextual feature information; and 4) a two-step model approach including initial separation into conifer and deciduous groups will result in higher overall accuracies.

Methods

Study Area

This study was carried out on the Acadia Research Forest (ARF) located in Noonan, New Brunswick (Figure 1; 45°59'26.22" N, 66°21'44.71" W). Loucks (1962) classified this region as the Maritime Lowlands Ecoregion, and Rowe (1972) as the Eastern Lowlands. Soils are typically poorly drained and topography is relatively flat (Loucks 1962). Predominant species occurring in this ecoregion are balsam fir (*Abies balsamea* (L.) Mill.), red spruce (*Picea rubens* Sarg.), black spruce (*Picea mariana* (Mill.) B.S.P.), eastern hemlock (*Tsuga canadensis* (L.) Carrière), eastern white pine (*Pinus strobus* L.), red maple, jack pine (*Pinus banksiana* Lamb.) in sandy areas, white spruce (*Picea glauca* (Moench) Voss) and American beech (*Fagus grandifolia* Ehrn.) (Loucks 1962). Elevations in the study area range from 13 m in the

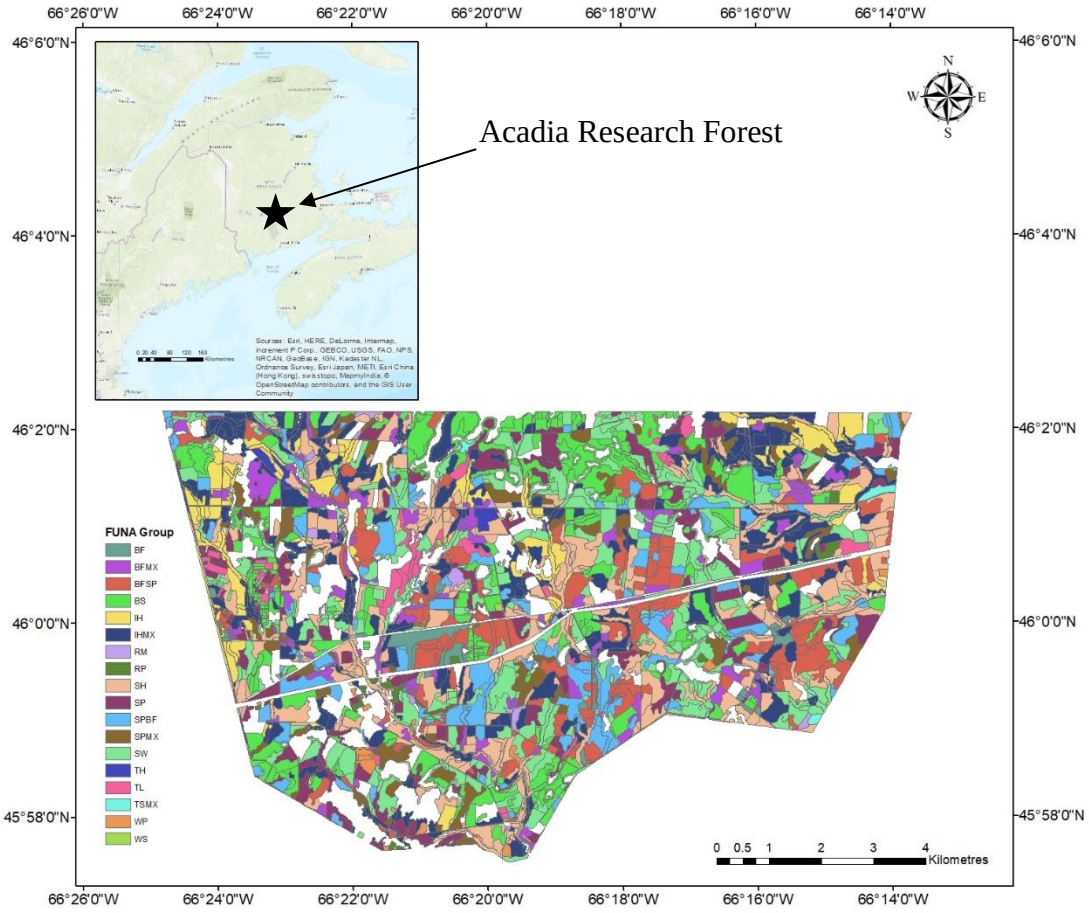

Figure 1: Location of the ARF east of Fredericton, New Brunswick. Note the many tree species present across the landbase. (FUNA = Forest Unit Name).

southern portion to 131 m in the north. According to Environment and Climate Change Canada's on-site climate data (Weather Station No. 8100100), the average annual temperature (1981-2010) was 5.2 degrees Celsius with an average annual precipitation of 1176 mm (Environment and Climate Change Canada 2019).

LiDAR Data

For this study, leaf-on data acquired in 2012 at an average of 1 pulse per m^2, and

leaf-on data acquired at 6 pulses per m^2 acquired in 2015 were used (Table 1). The associated LAS data files were processed and delivered by the service provider in 1 km^2 tiles. The 2012 data were delivered directly to the Canadian Forest Service and the 2015 data was acquired from the New Brunswick Department of Energy and Resource Development.

Table 1: Airborne LiDAR acquisition metadata.

	ARF 1 pulse per m^2	**ARF 6 pulses per m^2**
Flight date(s)	September 25, 2012	August 2-September 28, 2015
Foliage status	Leaf-on	Leaf-on
Average flying height (m)	1000 m	1000 m
Type of LiDAR sensor	Riegl Q680i	Riegl Q780i
Percent Overlap	50	50
Horizontal accuracy (m)	0.250	0.257
Vertical accuracy (m)	0.214	0.123

Crown Delineation/Segmentation

To facilitate crown delineation on tile edges, all LAS data files were re-tiled into datasets containing 20 metre overlaps on all sides. LAS returns were then normalized to the ground, resulting in z-coordinates corresponding to return heights relative to the ground. Canopy height models (CHMs) were then generated for both 1 pulse per m^2 and 6 pulses per m^2 datasets with raster cell sizes of 50 cm and 25 cm, respectively. Cell sizes were determined according to SEGMA software developer's recommendations (St-Onge 2018, pers. comm.). LASTools software (Isenburg 2017) was used in steps leading up to and including the creation of the CHMs. Prior to crown segmentation, spikes and pits in the CHMs were filled using an open source algorithm developed by St-Onge (2008).

Using the normalized and pit-filled CHMs as input, tree crowns were delineated across the ARF with SEGMA v 0.3.0 software (St-Onge 2018)). The underlying algorithm uses adaptive Gaussian filtering to first smooth the rasterized CHM, followed by locating the local maxima (assumed to be the maximum heights of individual trees). Maxima were then used as seeds for growing the crown region until stopping conditions are met (Yoga et. al. 2017). St-Onge et al. (2015) provide a detailed explanation of the algorithm. Crowns were delineated using first pulse returns from both the 1 pulse per m^2 and 6 pulses per m^2 data, producing two distinct polygon shapefiles (Figure 2). The workflow as shown in Figure 3 depicts how raw LAS files were prepared and transformed into CHMs for input into SEGMA v 0.3.0 software (St-Onge 2018).

Training Crown Selection

Fourteen tree species common to the Acadian Forest Region (Hosie 1979) were selected for investigation, including seven softwood species [balsam fir, black spruce, red spruce, white spruce, white pine, red pine (*Pinus resinosa* Ait.), tamarack (*Larix laricina* (Du Roi) K. Koch] and seven hardwood species [red maple, largetooth aspen (*Populus grandidentata* Michx.), trembling aspen (*Populus tremuloides* Michx.), sugar maple (*Acer saccharum* Marsh.), white birch (*Betula papyrifera* Marsh.), yellow birch (*Betula alleghaniensis* Britt.) and white ash (*Fraxinus americana* L.)]. For both 1 pulse per m^2 and 6 pulses per m^2 datasets, a minimum of 40 training crowns per target species were selected in the field for model calibration throughout the ARF. In total, 822 training crowns were selected for the 1 pulse per m^2 dataset and 906 for the 6 pulses per m^2 dataset.

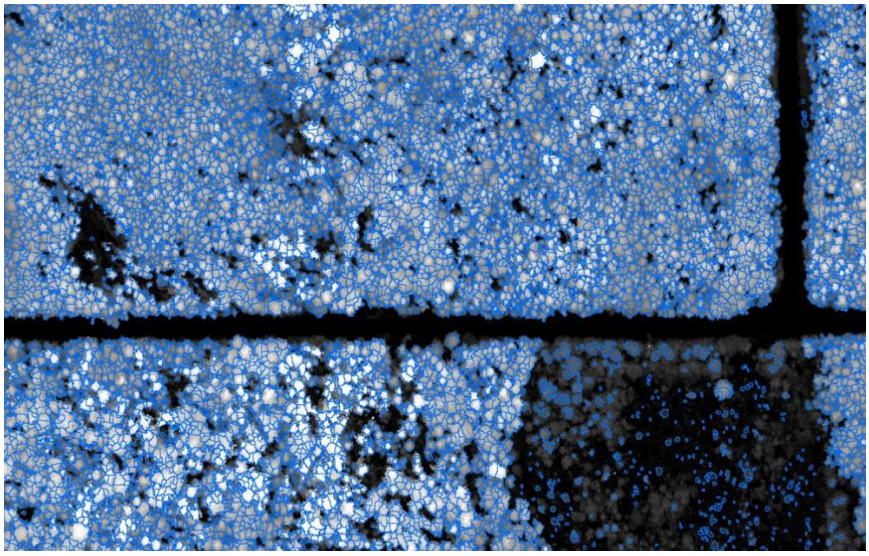

Figure 2: Individual tree crown delineations using SEGMA software overlaid on a CHM derived from 6 pulses per m^2 airborne LiDAR (Scale=1:2000).

Using the SEGMA polygon delineations, well-defined crowns were chosen in the

field from dominant/codominant trees distributed throughout a range of heights. Selected trees were limited to a minimum of 5 metres in height and 9 cm diameter at breast (1.3 m) height (DBH). A Geneq SX-Blue II GPS/GLONASS receiver attached via Bluetooth to a Panasonic Toughpad and ArcPad software, was used to geolocate the training crowns. For each selected tree crown, species, total height, height to the base of live crown and DBH were measured and recorded using a Haglöf Vertex IV hypsometer and a diameter tape.

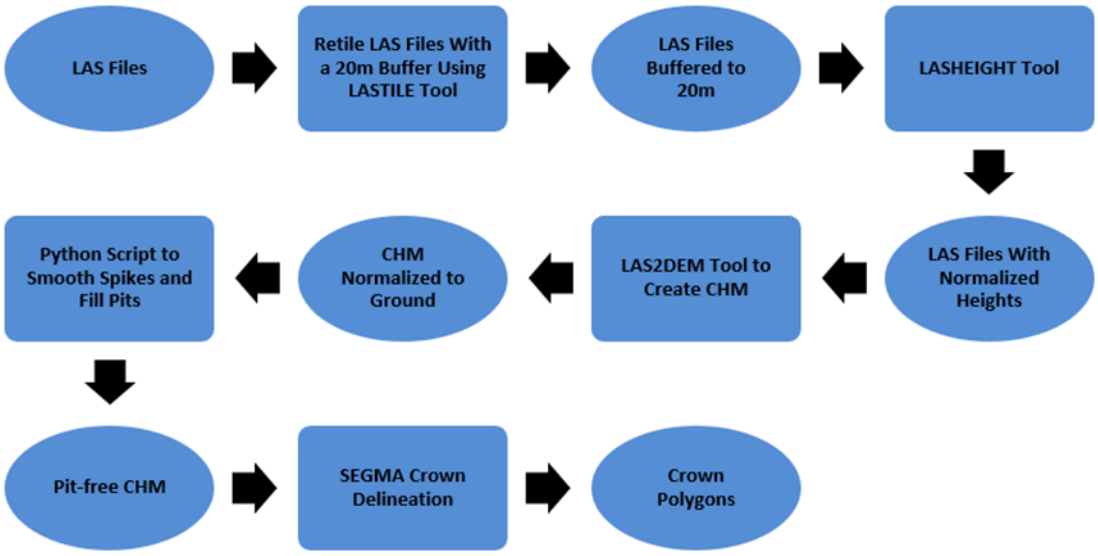

Figure 3: Workflow for the delineation of crown polygons.

Point Cloud Extraction and Calculation of Features

LiDAR points that fell within the identified training crown polygons were then extracted for feature calculation (Figure 4). From these clipped point clouds, individual 3D (geometric) and intensity crown metrics as presented in Tables 2 and 3 were calculated.

Random Forests Classification

The RF package (Breiman 2001) in the R programming language (R Core Team 2020) was used to classify tree species based on crown features sampled across 14 species. The RF algorithm builds a large number of decision trees, each from a different bootstrapped sample of crown observations. Remaining data excluded from each tree is used for validation and is commonly referred to as *out of bag* observations, or OOB. Tree nodes are partitioned recursively by identifying the predictor variable-value split that divides the data into the two most distinct groups, using a random subset of the potential predictor variables at each node, until a single observation remains in each node. Splits are determined by the Gini impurity index which is the difference in classification error between each divided node and its parent node. Class responses are then predicted for each observation using the subset of decision trees that excluded the observation during partitioning. OOB predictions in relation to their observed values are compared across all observations, thus quantifying the prediction accuracy of the ensemble of decision trees. The output model, or R object is stored and can then be used to make predictions on other datasets. Assuming crown samples are independent, 'out of bag' accuracy estimates can approximate accuracy estimates from an independent validation dataset (Yu at al. 2014).

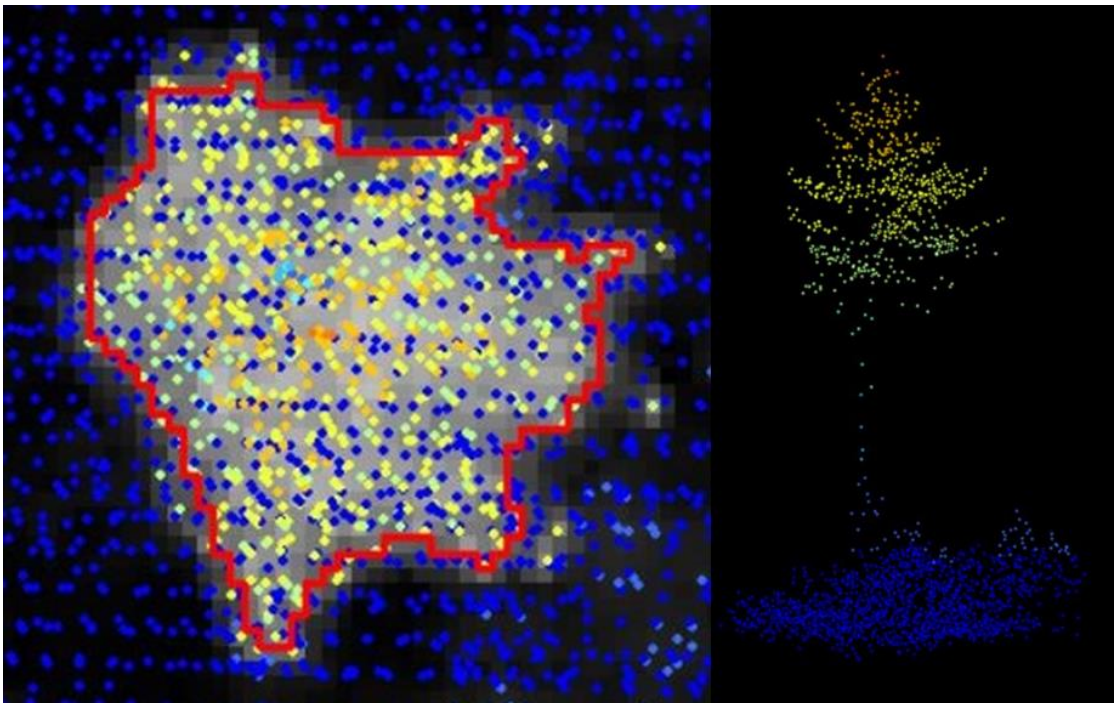

Figure 4: SEGMA crown delineation of a single white pine (left) and the isolation of the same white pine point cloud (right) derived from 6 pulses per m^2 ALS.

Table 2: Description of features based on geometric point distribution. Adapted from Prieur et al. 2022.

Symbol	Description	Return Types	Statistics
DI	Dispersion (coefficient of variation of return heights)	all, 1st	cv
SLOPE	Slope of the lines connecting the highest return to each of the other returns	all, 1st	mn, sd, cv, p25, p50, p75
RB	Ratio of the number of returns in different height bins (% of height) over total number of returns	all	Counts: 60_80, 80_90, 90_100, 95_100
CH	Ratio of the convex hull volume over maximum height cubed	all	N/A
RM	Ratio between different statistics and different types of return	all, 1st, 2nd	mn, p50

Abbreviations: all = all returns, 1st = first returns, 2nd = second returns, cv = coefficient of variation, mn = mean, sd = standard deviation, p = percentile.

Table 3: Description of features based on intensity measures. Adapted from Prieur et al. 2022.

Symbol	Description	Return Types	Statistics
DI	Dispersion (coefficient of variation of intensity)	1st	sd, cv
PE	Intensity values at given height percentiles	1st	p5, p10, p25, p50, p75, p90, p95
MI	Mean intensity of returns between interval of percentiles	1st	mn: all, p5_95, p10_90,
RM	Ratio between different statistics	all, 1st, 2nd	mn, p50

Ørka et al. (2012) and Korpela et al. (2010) suggested that only minor differences separate linear classification methods and RF when classifying Scandinavian tree species. This is consistent with the findings of Ørka et al. (2009), whereby results from RF classification methods were similar to those of support vector machines (SVMs) and linear discriminant analysis (LDA). Internal tests showed that RF performed better than SVM and k-nearest neighbor (KNN) algorithms on similar data, which is consistent with the results of Latifi et al. (2015). Perron (2018) used a RF approach to classify 10 Acadian forest species, demonstrating its suitability in complex species scenarios.

Crown Height

To determine if height plays a role in prediction accuracy, various models were developed for both 1 pulse per m^2 and 6 pulses per m^2 datasets. Due to the limited range of heights available for certain species, stratification was limited to two height classes, crowns under 15 metres and those greater than and equal to 15 metres. Results were summarized into confusion matrices.

Strategies to Improve Classification Accuracy

In addition to comparing classification results using 3D and intensity features derived from both 1 and 6 pulses per m^2 LiDAR data, I investigated the incorporation of contextual features such as elevation class, depth to water class, and black spruce class into classification models using the 6 pulses per m^2 dataset. Species groups/product classes as outlined in Table 4 and Type (Hardwood/Softwood) were chosen as appropriate to model, ensuring a well-distributed range of contextual classes were represented across the study area.

Table 4: Groupings of species by product.

Group	Species
Spruce/fir	balsam fir, black spruce, red spruce and white spruce
Tolerant hardwoods	sugar maple, red maple, yellow birch and white ash
Intolerant hardwoods	white birch, trembling aspen, largetooth aspen
Tamarack	tamarack
Red pine	red pine
White pine	white pine

A multi-step modeling approach to classification was also investigated through the application of three separate models. The first step was to use 3D, Intensity and Contextual Features to separate crowns into hardwoods and softwoods, herein referred to as the 'Type' model. Once hardwood and softwood crowns were separated, a second level of modeling was used to predict individual hardwood species separately from individual softwood species. Results were summarized in confusion matrices and features ranked according to their relative strength.

Independent Field Validation

In addition to the iterative data splitting approach as used in RF classification, Fassnacht (2016) recommended using an independent dataset for validation. To conduct independent validation of species groups, existing Continuous Landscape Inventory (CLI) plot data were used. The Canadian Wood Fibre Centre began establishing these plots at the ARF in 2018. A total of 135 plots were selected throughout this systematically spaced (500 m) inventory grid of 400 m^2 plots. This sampling design is similar to the provincial forest inventory grid being used by the New Brunswick Department of Energy and Natural Resources but at a finer scale (Dick 2018, pers. comm.).

RF model predictions were applied to the delineated crown polygons that corresponded to the selected CLI validation plots. Total predicted crown area by species group was calculated by summing the crown areas to the plot (400 m^2) level. Comparatively, total crown area by species group was derived using field-measured DBH and applying equations developed by Russell and Weiskettel (2011) and totaled. Predicted crown area was plotted against field-measured crown area and summarized.

Results

Pulse Density

Classification accuracies were compared between the 1 pulse per m^2 and 6 pulses per m^2 datasets. The 6 pulses per m^2 data yielded superior results at all modeling levels (Table 5). Overall accuracy was 11.1 % higher at the species level, 8.3 % higher at the genus level and species combined into similar product groups showed 10.3 % higher accuracy when using the 6 pulses per m^2 dataset. When separating hardwoods and softwoods as type, the 6 pulses per m^2 model correctly classified crowns at a rate of 7 % higher than the 1 pulse per m^2 model.

Table 5: Comparison of overall classification accuracies using 1 pulse per m^2 and 6 pulses per m^2 airborne LiDAR data.

Classification Modeling Level (n)	Overall Accuracy (%)	
	1 pulse per m^2	6 pulses per m^2
Species (14)	32.8	43.9
Genus (8)	41.4	49.7
Species group (6)	50.5	60.8
Type (2)	77.4	84.4

When comparing confusion matrices at the species level (Table 6), the majority of species showed higher classification accuracy for the 6 pulses per m^2 LiDAR data. Balsam fir and the spruce species showed the greatest increase in accuracy between 15.9 to 42 %. Sugar maple saw a 17 % gain in performance, and largetooth aspen, trembling aspen, tamarack, red maple and white pine all recorded lesser improvements between 3 and 8 %. In contrast, some species had reduced accuracy when modeled with the 6 pulses per m^2 dataset. Red pine, white ash, white birch, and yellow birch accuracy did not

improve with the higher LiDAR pulse density, ranging from 2 to 20 % better classification with the lower 1 pulse per m^2 dataset. Kappa scores (Cohen 1960) showed that both the 1 pulse per m^2 and 6 pulses per m^2 confusion matrices were considered to be in fair agreement, at 0.29 and 0.37, respectively. Species classification accuracy according to LiDAR pulse density is summarized in Figure 5.

Table 6: Confusion matrices for the RF classification of 14 tree species using a) 1 pulse per m^2 and b) 6 pulses per m^2 airborne LiDAR data. Actual species labels appear in the first column and predicted species are across the top row. BF = balsam fir, BS = black spruce, LTA = largetooth aspen, RM = red maple, RP = red pine, RS = red spruce, SM = sugar maple, TAM = tamarack, TA = trembling aspen, WA = white ash, WB = white birch, WP = white pine, WS = white spruce and YB = yellow birch. UA = User's Accuracy and PA = Producer's Accuracy.

a) 1 pulse per m^2 LiDAR

Species	BF	BS	LTA	RM	RP	RS	SM	TAM	TA	WA	WB	WP	WS	YB	Total	UA (%)
BF	**10**	7	0	0	1	2	2	3	0	2	2	3	2	2	36	**27.8**
BS	7	**14**	0	1	1	9	1	6	2	0	1	2	3	0	47	**29.8**
LTA	2	1	**8**	3	1	0	1	1	6	8	1	1	1	5	39	**20.5**
RM	0	1	4	**6**	1	1	4	2	3	5	4	7	3	11	52	**11.5**
RP	0	1	1	1	**25**	2	0	3	1	1	0	3	2	0	40	**62.5**
RS	4	8	1	2	3	**6**	1	16	1	1	2	5	3	2	55	**10.9**
SM	1	0	3	3	0	3	**16**	2	1	7	1	1	0	3	41	**39.0**
TAM	4	4	1	0	5	12	1	**31**	7	0	2	2	1	1	71	**43.7**
TA	1	3	9	3	7	2	0	5	**15**	3	2	4	3	0	57	**26.3**
WA	0	1	3	1	0	2	6	1	1	**20**	2	2	0	1	40	**50.0**
WB	4	2	4	1	4	1	0	4	1	6	**9**	6	2	7	51	**17.6**
WP	1	4	0	4	2	4	1	2	1	0	1	**37**	0	1	58	**63.8**
WS	3	5	2	4	5	3	3	5	4	1	3	2	**7**	3	50	**14.0**
YB	0	0	3	1	2	0	7	2	1	3	1	2	5	**20**	47	**42.6**
Total	37	51	39	30	57	47	43	83	44	57	31	77	32	56	684	
PA (%)	**27.0**	**27.5**	**20.5**	**20.0**	**43.9**	**12.8**	**37.2**	**37.3**	**34.1**	**35.1**	**29.0**	**48.1**	**21.9**	**35.7**		
Kappa	0.29															

b) 6 pulses per m^2 LiDAR

Species	BF	BS	LTA	RM	RP	RS	SM	TAM	TA	WA	WB	WP	WS	YB	Total	UA (%)
BF	**67**	13	1	0	0	10	0	7	0	2	1	8	4	1	114	**58.8**
BS	13	**32**	1	2	0	10	2	4	0	1	0	2	3	0	70	**45.7**
LTA	0	3	**12**	1	1	1	1	11	8	2	5	1	1	4	51	**23.5**
RM	2	0	1	**9**	4	2	6	3	4	4	2	5	3	6	51	**17.6**
RP	0	1	2	3	**22**	3	1	6	1	0	2	4	7	0	52	**42.3**
RS	7	5	1	2	2	**46**	0	13	1	1	0	6	3	0	87	**52.9**
SM	1	0	0	2	0	0	**23**	0	0	5	1	0	2	7	41	**56.1**
TAM	5	1	1	0	2	9	0	**51**	1	0	3	2	22	1	98	**52.0**
TA	1	0	11	1	4	0	1	6	**19**	2	5	2	1	3	56	**33.9**
WA	0	0	0	2	0	0	6	1	6	**14**	5	0	4	4	42	**33.3**
WB	1	4	5	2	4	1	1	12	7	3	**5**	3	0	7	55	**9.1**
WP	3	0	0	2	2	4	2	0	0	1	0	**44**	4	0	62	**71.0**
WS	6	4	1	0	11	1	2	8	0	0	1	3	**40**	0	77	**51.9**
YB	0	0	1	0	0	1	9	2	4	6	1	1	0	**17**	42	**40.5**
Total	106	63	37	26	52	88	54	124	51	41	31	81	94	50	898	
PA (%)	63.2	50.8	32.4	34.6	42.3	52.3	42.6	41.1	37.3	34.1	16.1	54.3	42.6	34.0		
Kappa	0.37															

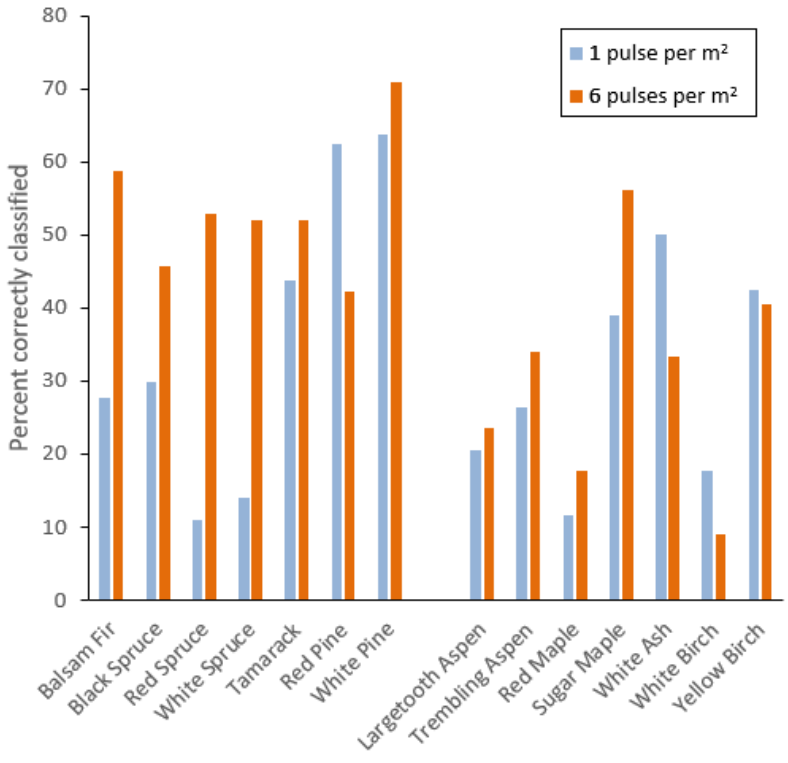

Figure 5: Comparison of species classification accuracies derived from 1 pulse per m^2 and 6 pulses per m^2 airborne LiDAR data.

Crown Height

I investigated effects of tree height on individual species classification by comparing classification accuracies for two height classes (< 15 m and ≥ 15 m) at the two pulse densities (1 pulse per m^2 and 6 pulses per m^2), each at two sampling sizes ($n \geq 10$ and $n \geq 20$) because of small sample size for some species. As shown in Table 7, the 6 pulses per m^2 performed better in all cases, with the greatest increases in accuracy for trees less than 15 m tall in the large sample ($n \geq 20$) group, which improved by 25.5 % over the 1 pulse per m^2. Trees greater than 15 m in height similarly recorded an increase of 20.4 % higher accuracy with the higher LiDAR dataset. In the small sample group ($n \geq 10$), accuracy increased 12.5 % for trees less than 15 m tall and 13.6 % for trees at or exceeding 15 m.

In the 1 pulse per m^2 dataset with the smaller sample ($n \geq 10$), all but three (out of seven) species performed better when taller trees (15 m and greater) were used. For red spruce, trembling aspen, white birch, and white pine, accuracy increased between 9.1 and 34.2 %. In contrast, red maple, tamarack and white spruce accuracies were between 3.9 and 9.0 % lower when the taller trees greater than 15 m were used. In the 1 pulse per m^2 dataset with the larger sample ($n \geq 20$) group, all species tested with the exception of tamarack showed higher accuracy when training crowns at least 15 m in height were used. Red spruce, white birch and white spruce recorded improvements ranging from 4.3 and 25.9 % while the accuracy in tamarack declined by 10.7 %.

In the 6 pulses per m^2 dataset with the smaller sample ($n \geq 10$), all but three (out of eight) species performed better when taller trees (15 m and greater) were used. Balsam

fir, black spruce, red maple, white birch and white spruce improvements in accuracy ranged from 1.2 to 53.3 % while largetooth aspen, red spruce and tamarack declined in accuracy between 2.2 and 22.4 %.

Table 7: Comparison of classification accuracy by individual species using training crowns less than 15 m in height and those 15 m and greater. Refer to Table 6 for species abbreviations.

LiDAR Dataset	Class	Species	User's Accuracy (%)	
			Crowns <15 m (n)	Crowns ≥ 15 m (n)
1 pulse per m^2	≥ 10	RM	33.3 (15)	24.3 (37)
		RS	26.1 (23)	40.6 (32)
		TAM	40.9 (44)	37.0 (27)
		TA	28.6 (14)	62.8 (43)
		WB	13.0 (23)	28.6 (28)
		WP	58.3 (12)	67.4 (46)
		WS	21.4 (28)	13.6 (22)
1 pulse per m^2	*≥10*	*Average*	*31.7*	*39.2*
1 pulse per m^2	≥ 20	RS	26.1 (23)	40.6 (32)
		TAM	47.7 (44)	37.0 (27)
		WB	34.8 (23)	60.7 (28)
		WS	32.1 (28)	36.4 (22)
1 pulse per m^2	*≥20*	*Average*	*35.5*	*43.7*
6 pulses per m^2	≥ 10	BF	55.9 (93)	76.2 (21)
		BS	41.8 (55)	60.0 (15)
		LTA	53.8 (13)	39.5 (38)
		RM	14.3 (14)	67.6 (37)
		RS	59.2 (49)	36.8 (38)
		TAM	56.4 (39)	54.2 (59)
		WB	12.0 (25)	26.7 (30)
		WS	60.0 (10)	61.2 (67)
6 pulses per m^2	*≥10*	*Average*	*44.2*	*52.8*
6 pulses per m^2	≥ 20	BF	79.6 (93)	71.4 (21)
		RS	61.2 (49)	42.1 (38)
		TAM	59.0 (39)	76.3 (59)
		WB	44.0 (25)	66.7 (30)
6 pulses per m^2	*≥20*	*Average*	*61.0*	*64.1*

In the 6 pulses per m^2 dataset with the larger sample ($n \geq 20$) group, out of four species, tamarack and white birch accuracy increased 17.3 and 22.7 % respectively, when taller trees (15 m and greater) were used, while it declined for balsam fir by 8.2 % and red spruce by 19.1 %.

Species Groups and the Addition of Contextual Layers

After aggregating individual species into 6 species groups using the 6 pulses per m^2 dataset, overall classification accuracy improved to 60.8 %. The incorporation of elevation, depth to water and black spruce affinity contextual features further increased accuracy to 67.7 %.

Through grouping by species and adding contextual features, all user accuracies increased compared to their individual accuracies. Gains were between 3.2 % (to 74.2 %) for White pine and 37.1 % (to 59.3 %) for Intolerant hardwoods (Table 8). White pine was primarily confused with Spruce/Fir. The Intolerant hardwoods group was often confused with Tamarack and Tolerant hardwoods. Tamarack's gain was 16.4 % (to 68.4 %) and was most often confused with Spruce/fir. Red pine accuracy increased by 9.6 % (to 51.9 %) and was mostly confused with Tamarack. Spruce/fir was mostly confused with Tamarack with an accuracy gain of 18.4 % (to 70.7 %). Tolerant hardwoods group was mostly confused with Intolerant hardwoods and Spruce/fir where user accuracy increase by 34.7 % to (71.6 %).

Table 8: Confusion matrix for 6 species groups classified using 6 pulses per m^2 airborne LiDAR data. UA = User's Accuracy and PA = Producer's Accuracy.

Species group	Intolerant hardwoods	Tamarack	Red pine	Spruce/ fir	Tolerant hardwoods	White pine	Total	UA (%)
Intolerant hardwoods	**96**	29	6	8	16	7	162	59.3
Tamarack	4	**67**	2	21	2	2	98	68.4
Red pine	5	8	**27**	2	4	6	52	51.9
Spruce/fir	4	43	17	**246**	17	21	348	70.7
Tolerant hardwoods	18	6	6	14	**126**	6	176	71.6
White pine	1	1	3	7	4	**46**	62	74.2
Total	128	154	61	298	169	88	898	
PA (%)	75.0	43.5	44.3	82.6	74.6	52.3		
Kappa	0.61							

Hierarchical Modeling

After separating the hardwoods and softwoods using the Type model with the added contextual features, the Hardwood model yielded an overall accuracy of 83.8 % and kappa score of 0.69 which is considered a substantial agreement (Cohen 1960) (Table 9). The Intolerant hardwoods group classification was 23.4 % higher (59.3 % to 82.7 %) in accuracy than the single hardwood group model. Tolerant hardwoods group classification was 13.6 % higher (71.6 % to 85.2 %) in accuracy than the single hardwood group model.

Table 9: Confusion matrix for the hardwood model separated into intolerant and tolerant hardwood groups. UA = User's Accuracy and PA = Producer's Accuracy.

Species group	Intolerant Hardwoods	Tolerant Hardwoods	Total	UA (%)
Intolerant Hardwoods	**134**	28	162	82.7
Tolerant Hardwoods	26	**150**	176	85.2
Total	160	178	338	
PA (%)	83.8	84.3		
Kappa	0.69			

The Softwood model had an overall accuracy of 71 % and a kappa score of 0.64. (Table 10). Differences in classification accuracies between the single and sequential models were minimal for tamarack, spruce/fir and white pine groups ranging from a decline of 0.3 % to an increase of 3.1 %. Red pine classification improved by 11.6 % compared to the single group model.

Table 10: Confusion matrix for the softwood model separated into four softwood species groups. UA = User's Accuracy and PA = Producer's Accuracy.

Species group	Tamarack	Red pine	Spruce/fir	White pine	Total	UA (%)
Tamarack	**70**	3	23	2	98	71.4
Red pine	9	**33**	4	6	52	63.5
Spruce/fir	51	27	**245**	25	348	70.4
White pine	1	6	8	**47**	62	75.8
Total	131	69	280	80	560	
PA (%)	53.4	47.8	87.5	58.8		
Kappa	0.64					

Feature Importance

Feature variables were ranked by importance using the *varImpPlot* function in the RF package in R. The mean of a feature's total decrease in node impurity, weighted by the proportion of samples reaching a node in each individual RF decision tree, is referred to Mean Decrease Gini (Brieman 2001). As shown in Figure 6, the most important feature variables for both the softwood- and hardwood-specific group models were Intensity of first return at the 90 percentile (I_PE_1st_p90); refer to Tables 2 and 3 for a description of naming convention. The softwoods-specific model (a) also relied on 3D features including various ratios between statistics and slopes. In the hardwood-specific model (b), following the top intensity feature, all three of the introduced contextual features ranked as highly important.

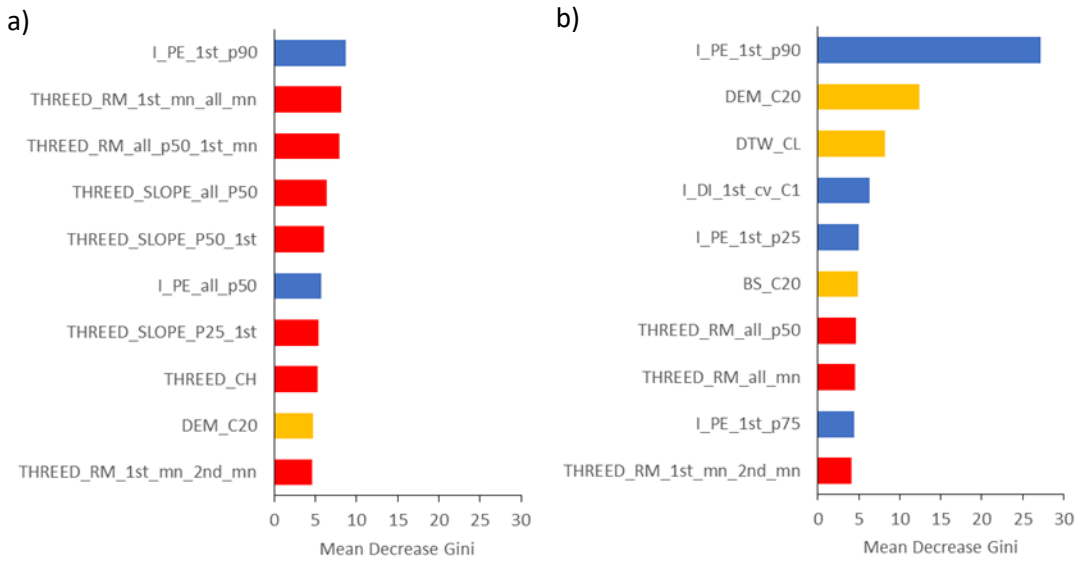

Figure 6: Ranking of 10 most important features as Mean Decrease Gini in the hierarchical (a) softwood and (b) hardwood species group classification modeling derived from 6 pulses per m^2 airborne LiDAR data. Variables include 3D (red), Intensity (blue) and Contextual (yellow) features.

DEM_C20 = Digital elevation model class, DTW_CL = Depth to water class and BS_C20 = Black spruce species affinity class.

Field Validation

Figure 7 displays the relationship between CLI calculated crown area and LiDAR predicted crown area for the 135 field validation plots through simple linear regression. The Spruce/fir group (Figure 7a) showed a moderate positive relationship with an R^2 of 0.44 (F = 104.2, P < 0.001). Other species groups with moderate positive relationships were White pine (Figure 7d) with R^2 = 0.40 (F = 88.58, P < 0.001) and the Tolerant hardwoods group (Figure 7f) with R^2 = 0.53 (F = 149.3. P < 0.001). The remaining species groups had notably weaker relationships. Tamarack (Figure 7b) had an R^2 of 0.12 (F = 17.56, P < 0.001), while Red pine (Figure 7c) posted an R^2 of 0.01 (F = 1.312, P = 0.254), and finally, for the Intolerant hardwoods group (Figure 7e) R^2 = 0.002 (F = 0.297, P = 0.586). Despite the fact that some species groups showed weak predicted to observed crown area relationships, the dominant predicted species group in each of the 135 field plots agreed with the field observed species group 64 % of the time. On the broader forest level, Table 11 shows the ratios of predicted and observed crown areas relative to total crown area for each species group. Forest level bias ranged from 1.7 % for the White pine group to a high of 15.1 % for Spruce/fir, with an average of 8.7 % across all species groups.

Table 11: Comparison of field observed and LiDAR predicted crown areas relative to total measured crown area for 6 species groups.

Species Group	Field Crown Area Ratio	Predicted Crown Area Ratio	Difference (%)
Spruce/fir	0.55	0.40	15.1
Tolerant hardwoods	0.33	0.22	11.2
Intolerant hardwoods	0.04	0.15	11.2
Tamarack	0.03	0.13	10.3
Red pine	0.00	0.03	2.9
White pine	0.05	0.07	1.7

Summary of Model Performance

Accuracy of species prediction models developed using RF classifiers are summarized in Figure 8. Classification accuracy was improved through a variety of models and approaches. Increasing pulse density from 1 to 6 pulses/m^2 resulted in higher accuracy at both the individual species (11.1 %) and species group levels (10.3 %), comparing Figure 8a and 8b. Furthermore, with the addition of contextual features and using a hierarchical approach (first separating hardwoods and softwoods and then dividing each into groups), overall accuracy improved by 10.3 % for softwood groups and 23 % for hardwood groups (Figure 8b and 8c).

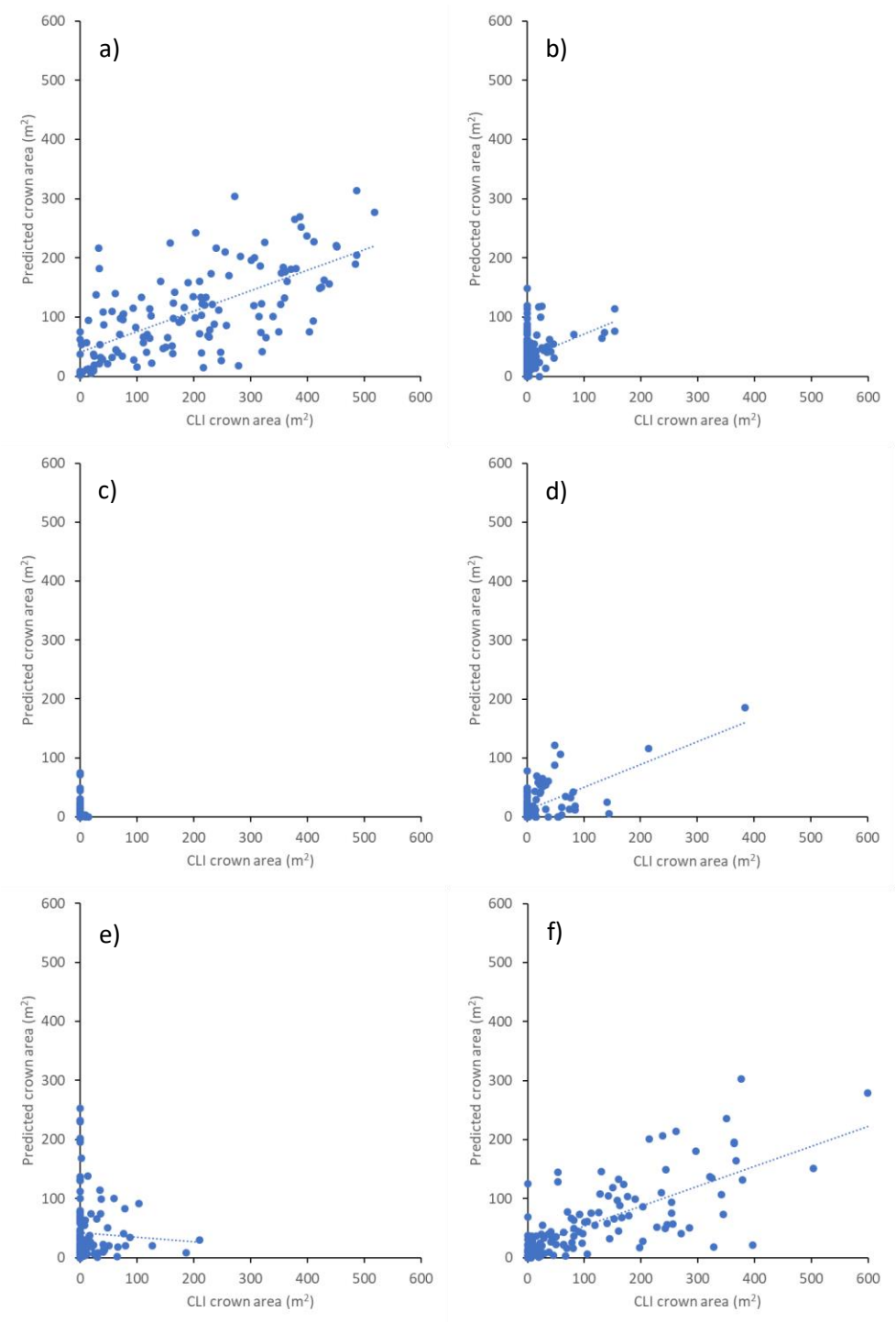

Figure 7: Comparisons of LiDAR predicted crown area with Continuous Landscape Inventory (CLI) plots through simple linear regression. Species groups are displayed as follows: a) Spruce/Fir, b) Tamarack, c) Red pine, d) White pine, e) Intolerant hardwoods, and f) Tolerant hardwoods.

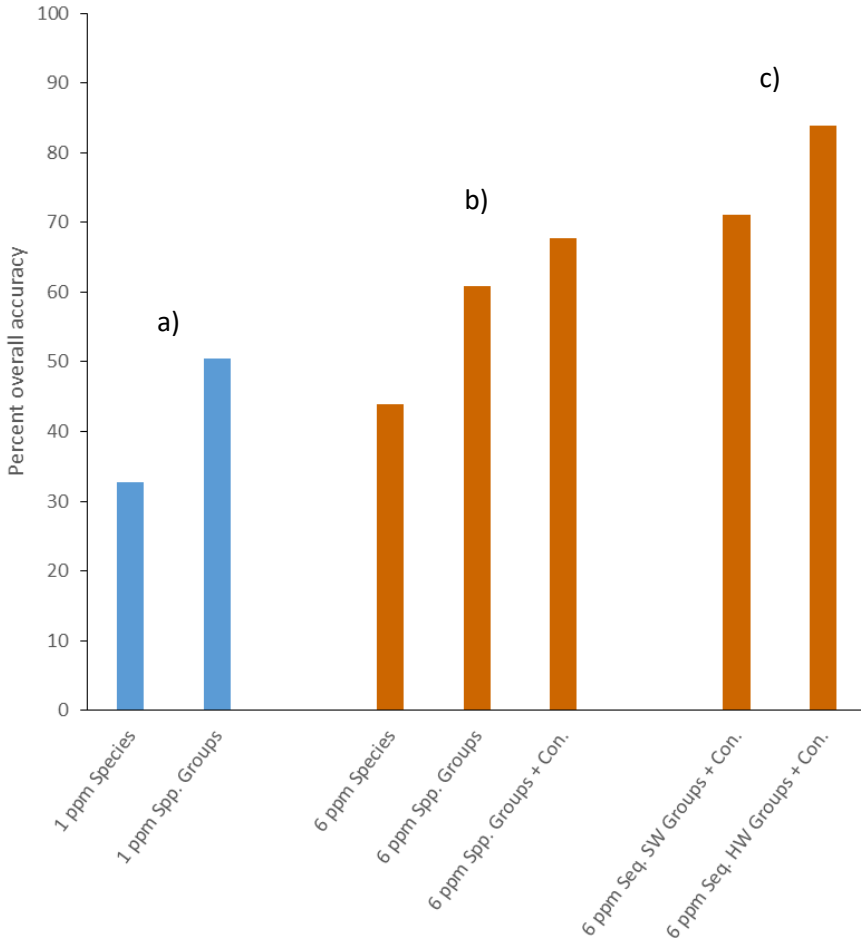

Figure 8: Overview of accuracy of RF classification models used in this study: a) 1 and 6 pulses/m^2, b) for Species (Spp.), Species Groups, and Species Groups with contextual (Con.) variables added, and c) first divided into hardwood (HW) and Softwood (SW) types and then into SW and HW groups.

Discussion

This study evaluated how several factors contribute to improving species classification using airborne LiDAR. Many factors are at play throughout the classification process including LiDAR acquisition pulse density, crown height and quality of crown delineation, grouping of species, variables selected for modeling, the aggregation of prediction classes, and finally the number of modeling levels. Through progressively modeling these variables, it is possible to determine the impacts of different approaches and recommend ways to improve species classification.

Pulse Density

Pulse density is a key factor in providing the foundational input for remote species classification using LiDAR. The distribution of pulse returns provide a 'virtual scaffold' for the calculation of three dimensional crown geometry. Pulse density, therefore, becomes increasingly important as the target area becomes smaller. The lower, 1 point per m^2 LiDAR dataset used in this study resulted in fewer localized pulse returns in most training crowns. Due to this sparseness, multiple returns in small crown trees were frequently absent, thus excluding certain feature calculations that rely on ratios between the first and subsequent returns. Overall, the higher density 6 pulses per m^2 dataset showed 11.1 % better classification accuracy than 1 pulse per m^2 in predicting individual species. This finding is similar to several other studies relating to LiDAR pulse density and species classification (Reitberger et al. 2008; Yu et al. 2014; Hovi et al. 2016; Fussnacht et al. 2016). The higher number of returns produced a better-defined three-dimensional shape allowing for more accurate feature calculations and ultimately better

classification. Only four out of 14 species (red pine, white ash, white birch and yellow birch) failed to show higher classification accuracies with the 6 pulses per m^2 dataset. This possibly could be due to the large crown areas of these species, such that the 1 pulse per m^2 LiDAR captured sufficient detail of crown architecture. In a diverse Acadian forest containing a broad species mix and crown size, the 6 pulses per m^2 was superior overall.

LiDAR density as low as 0.5 pulses per m^2 has been shown to be effective in area-based forest inventory predictions in certain forest environments (Treitz et al. 2012). Jakubowski et al. (2013) found that some metrics used for area-based predictions are relatively unaffected until pulse density dips below 1 pulse per m^2. However, at the individual tree level of species classification, prediction units are typically much smaller, confined to single tree crowns, which necessitates higher density LiDAR pulse acquisition.

Confusion matrices indicated that balsam fir tended to be confused with other softwoods, primarily spruce species. The spruces and tamarack also were confused with balsam fir and other softwoods. This occurred for both the 1 pulse per m^2 and 6 pulses per m^2 datasets, and was likely because of the similarities in crown shape, size and structure among these species. Individual hardwood species were not accurately classified using either 1 pulse per m^2 or 6 pulses per m^2, being confused with not only other hardwoods but also softwood species. The more complex and non-uniform crowns of hardwoods make species identification challenging given their high variability of crown characteristics.

Crown Height

The more detailed pulse return of 6 pulses per m^2 aided in the determination of crown shapes and vertical distribution of pulse returns, ultimately resulting in better classification accuracies. Trees in both height classes tested benefited from the increased scanning coverage. Although not all species were represented in this analysis, this study showed that higher pulse density resulted in better accuracy. The number of height classes was limited to two so more research is warranted to determine effects of height on species identification.

Species Groups and the Addition of Contextual Layers

When trees were aggregated into several species groups and then classified using the 6 pulses per m^2 dataset, accuracy increased by 16.9 %. Six species groups were assigned as Spruce-fir: balsam fir, black spruce, red spruce and white spruce; Tolerant hardwoods: sugar maple, red maple, yellow birch and white ash; Intolerant hardwoods: white birch, trembling aspen, largetooth aspen; Tamarack; Red pine; and White pine. This grouping approach is effective when managing on a coarser level where individual tree identification is not required as part of the management objectives. Many forest products including structural lumber and pulp are marketed at the aggregate level such as SPF (spruce, pine, fir) graded lumber. Other products include wood chips derived from lower value hardwoods destined for pulp. High value sawlogs including veneer quality are often marketed from tolerant hardwood species used to construct furniture, cabinets and flooring. Red pine is commonly used for utility poles and white pine for construction and general use. (NLGA 2017; Maritime Lumber Bureau 2022; YSC Forest Products

Marketing Board 2022). In complex forests with many species present, this approach provides a method conducive to large-scale forest operations.

The incorporation of common species associations and their ecological and site requirements has been used by photo interpreters for decades in their decision process when identifying tree species (Sayn-Wittgenstein 1978). It therefore seems beneficial to incorporate some of this contextual knowledge into species classification modeling efforts. I incorporated elevation, depth to water and black spruce affinity into the species group model. This analysis was limited to the species group level, due to a lack of training data at the individual tree level for some species. Having sufficient training data representing a variety of classes is important to ensure reliable classification. The addition of contextual features resulted in a further increase of 6.9 % in classification accuracies at the species group level.

Hierarchical Modeling

The hierarchical or sequential modeling approach proved effective to maximize classification accuracies. Even though it added some complexity, product groups were classified to levels closer to operational usability using this approach. Separating hardwoods and softwoods in the first level of modeling improved results, and the hardwood group model performed especially well, increasing classification accuracy by 16.1 %. This was possibly because only two classification choices, the Intolerant and Tolerant hardwood groups, remained available for assignment. The softwood group model resulted in a 3.4 % gain over the single model. The softwood groups were reduced to four choices of Spruce/fir, Tamarack, Red pine and White pine with the remaining

confusion resting primarily between tamarack and spruce/fir. Visually, these short-needled species have markedly different characteristics than the long-needled pines. In future studies, further model refinement could be tested by separating species groups by physical characteristics with the ultimate goal of defining attributes at finer levels.

Feature Importance

I tried many features as modeling inputs, some of which had more of an influence than others in the resultant predictions. The hierarchical models using the product groups performed the strongest so this is where the discussion of feature importance will focus. The most important feature in both hardwood and softwood group models was a LiDAR intensity metric. Intensity was relatively more influential in the hardwood model. Three of the top five features were intensity. Contextual features such as elevation, depth to water, and black spruce affinity also proved to be important in the hardwood model. Hardwoods tended to be more irregular in crown shape, which may be the reason a greater emphasis was placed on the intensity and contextual features instead of the geospatial features. Furthermore, broadleaf species typically contain greater surface areas per unit area compared to coniferous species. The thicker walled and smaller compact cells of conifers reduce the interior scattering of light (Ustin and Jacquemoud 2020). In a landcover classification study using airborne LiDAR, Song et al. (2002) found the relative intensity of broadleaved trees was almost double that of conifers.

Although intensity was also the most important feature in the softwood model, the distribution of pulse returns throughout the crown was also important. Contextual features were less important for predicting softwood groups than for hardwood groups.

Softwood groups relied more on three dimensional features such as the shape and distribution of pulse returns.

Models developed using LiDAR intensity metrics come with certain limitations. During LiDAR acquisition, overlapping flight line regions exhibit excess noise (Yan and Shaker 2016). Such noise is mostly caused by various environmental factors or sensor and system specifications including range and scanning angle (Jelalian 1992; Wu at al. 2021). Therefore, intensity normalization may be required before the application of locally developed models to other forest areas.

Field Validation

After running predictions across the ARF using the hierarchical species group models, I validated the results at the plot level to see how well it could be applied operationally. Rolling up to an aggregated management unit such as the plot level (400 m^2) is often useful, depending on the management objective. When comparing plot level basal area from field measurement to species group crown area from the models, results showed weak to moderate relationships with R^2 values ranging from 0.00 to 0.53. Nevertheless, the predicted leading species assignment by plot was reasonably accurate, identifying the leading species nearly two-thirds of the time. The low accuracy at the plot level could be due to several factors. The crown delineation model SEGMA sometimes over-delineated crowns by separating single large spreading crowns into multiple polygons. Alternately, crowns in close proximity to one another sometimes were merged during delineation, resulting in an under-segmentation. Codominant crowns in high density stands may be especially susceptible when interlocking crowns are present,

making delineation difficult. Small and overtopped crowns are also susceptible to under-segmentation or omission. Over or under crown delineation will result in an over or under estimation of crown area by species. More precise crown delineation may be achieved through higher LiDAR pulse density than used in this study and should be investigated. SEGMA delineation and other alternate methods should be tested.

At the forest level, certain species groups performed better than others in field validations. Red pine and White pine groups, which made up a very small proportion of the total forest crown area, had very low biases between predicated and observed crown area ratios. Tamarack, Intolerant hardwoods, and Tolerant hardwoods groups also had relatively low biases all just over 10 %. Spruce/fir clearly had the highest crown area ratios of all groups for both predicted and observed, along with the highest bias at just over 15 %. From a forest level perspective, field validations show the need for further model improvement especially in the Spruce/fir group, which occupied the most crown area in the validation plots.

These results highlight the importance of independent field validation of modeling. The training crown data used in this study were well-defined, unlike many of the over/under delineated crowns within the field validation plots. Therefore, to reduce error when applying models for widespread predictions, one must be cognisant of the extent of any deviations or variability within training datasets.

Study Improvements

The study area contained a relatively small component of tolerant hardwoods, which made locating training crowns challenging. More training crowns identifying a broader range of crown conditions could result in higher accuracy classifications.

As this study demonstrated, intensity is a driving metric for species classification. The LiDAR datasets used were derived from a single spectral wavelength. Incorporation of multiple reflective values either through imagery or multispectral LiDAR might improve classification results.

Other ways to improve would be through the addition of more features including shape and distribution of point clouds, light intensity, and more contextual data. Another area to explore further is crown delineation methods that may provide better aggregation of points within crowns. The Acadian forest is complex with over 30 tree species present, and thus species classification may benefit from diverse data sources, including multiple LiDAR captures, contextual features, remote sensing data including aerial photography and satellite imagery, and prior local knowledge of the area of interest. Some species have distinct structural features while others, such as balsam fir and the spruce species, can be quite similar. As some satellite imagery becomes available multiple times per year, it may be possible to discern phenological characteristics invoked by seasonal change such as colour variation, bud burst, and flowering. For example, black spruce and white spruce can be easily differentiated during a 2-week or so period in the spring, due to later bud burst of black spruce. Similarly, red maple is very obvious due to flowering at certain times. These features may incorporated through a multi-step modeling approach through image captures and change detection throughout the growing season. The goal of

accurate remote species identification is challenging with many factors to consider. Every new piece of knowledge gets us closer to a solution that could be used to better manage our forest resources.

Conclusions

This study showed that 6 pulses per m^2 provided better overall classification accuracy compared to the 1 pulse per m^2 dataset. Larger trees greater than 15 m tall were better classified than smaller ones and intensity was the most important feature for classification using RF modeling. The addition of elevation, depth to water, and species affinity data improved classification accuracy. Furthermore, a hierarchical or sequential modeling approach proved to be a good approach to further improve classification and should be incorporated in future modeling efforts.

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